REACT: The Riskmap Evaluation and Coordination Terminal

by

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Submitted to the Department of Electrical Engineering and Computer Science
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Abstract

The United Nations Office for Disaster Risk Reduction (UNDRR) states that economic losses due to natural disasters have risen 151 percent in the past 20 years. Of these disasters, floods are the most common. The Sendai Framework for Disaster Risk Reduction was created by the UNDRR in order to chart goals for future risk mitigation; among its seven global targets is increasing the availability of disaster risk information and assessment systems. Disaster information systems use state of the art techniques such as remote sensing in order to mitigate damages from natural and man made hazards.

It is common in developed countries utilize networks of advanced sensors and ahead of time mapping in order to facilitate emergency responses; however, such systems are not available in developing countries due to cost limitations. The widespread proliferation of smart phones and social media use in developing countries means that citizens can be used as sensors by reporting disaster information online. The Riskmap system was developed by the Urban Risk Lab at MIT in order to gather citizen report streams. Such citizen disaster reports have two issues: a large influx of reports can cause information overload in emergency operations centers, which makes it difficult to summarize the situation. Machine learning has previously been used in order to analyze and simplify information for human consumption. This work seeks to use novel machine learning techniques to fully utilize crowd-sourced social media reports gathered using the Riskmap system.

Thesis Supervisor: Miho Mazereeuw
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To Aditya and Miho- not one page of this thesis could have been written without your help and your guidance. Thank you so much for your patience and your expertise.

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Chapter 1

Introduction

Natural disasters are a constant threat to societies all over the planet. Among natural disasters, flooding is the most common calamity in the world [1]. Flood related deaths account for half of all deaths from natural disasters [2]. Although flooding impacts both developed and developing countries, developing nations face much higher mortality rates as a result of flooding since they lack resources to adequately mitigate hazards [3, 4]. Deltaic megacities in developing countries are particularly at risk because unregulated urbanization, rising population and climate change are increasing the rate at which floods occur [1]. Moreover, there is little data that is available before, during, and after a disaster to help stakeholders mitigate hazards [5].

Various stakeholders, such as humanitarian NGOs, government emergency responders and affected citizens, have different but overlapping interests with regards to disaster management. Government and NGOs work together to provide relief and mitigate damages from flooding [6], while citizens look for relevant information and try to reduce their risk by avoiding heavily affected areas [7]. Information is at the core of disaster management; however, data scarcity makes it hard for emergency personnel to optimize their use of resources, while citizens have an abundance of information about their surroundings but must be careful not to trust incorrect or outdated information about broader areas [8].

Disaster information systems can connect affected communities with Emergency Operations Centers (EOCs), thereby bridging the information gap between responders and citizens. Many such disaster information systems have been developed, but they often suffer from a lack of institutional buy-in [9]. The lack of engagement can be partly attributed to the difficulty of adding data gathering responsibilities to emergency personnel that have little time during crises. Asking citizens to submit information is a solution to this problem; however, crowdsourcing brings its own issue: in times of crisis EOCs can suffer from information overload when they are presented with too much data [10].

The REACT system uses novel machine learning and human computer interaction research to reduce information overload from crowd sourced data in EOCs, thereby decreasing disaster response time. REACT classifies reports as indicating heavy flooding or not through an ensemble model. It extracts key features from each of the parts of a report (text, picture, metadata) using domain specific techniques and then uses a small dense neural net to classify the citizen report.

First we establish the motivation for using citizens as sensors and analyzing this noisy data using machine learning. We then review different machine learning techniques that have been used in crisis information systems, including those that also utilize social media. Finally a novel ensemble learning model is presented that can accurately predict large urban flood events from crowdsourced data.

Chapter 2

Background

Global climate change is 'expected to increase the frequency and intensity of floods' [4]. Developing urban areas that are undergoing unchecked development and rising population regularly experience flooding [1]. Nowhere is this more apparent than in South and Southeast Asia, where the severity of floods has been increasing over the past several decades [11].

Of the world's 33 mega-cities with population over 10 million, over 60 percent are located in developing Asian Countries [12]. These cities face a looming crisis as flood risk increases, but there are also unique opportunities for risk mitigation. Megacities are characterized by high population density, which leads to an increase in economic damages and loss of life during flood events, but it also means that there are large numbers of citizens that have disaster information they would like to share with others [1].

2.1 History of Disaster Informatics

One of the best known and earliest work in disaster informatics was John Snow's use of maps to find the source of the 1857 Cholera outbreak in London[13]. This example is taught to all students of epidemiology and illustrates the need not only for up to date information, but for systems that ease the analysis of this information. In John Snow's case, the map was the technology that allowed him to visualize the spread of the disease and effectively take action that ended the outbreak; however, the computer revolution has drastically changed the way that scientists and responders analyze disaster information. John Snow used mapping technology to track the spread of disease, but now researchers are using artificial intelligence to predict cholera outbreaks before they happen [14].

In more recent times, the need for Information Technology (IT) in disaster management has been clear since the mid 1980s when computers became user friendly enough to be used during disasters [15].

Now many Emergency Operations Centers (EOCs) use Geographic Information Systems (GIS), inventory control systems, and online messaging systems among other technology in order to organize spatial data and analyze disaster information. For example, Mozambique used an integrated disaster management system to provide early warning during the 2007 Zambezi floods, while Guatemala's inventory management helped to curb government bribes [9]. While technology has helped some EOCs to better respond to disaster events, researchers have often stated that 'there are many reasons to remain skeptical about the idea that technology will provide a panacea for emergency management problems' [16, 10, 17]. A number of potential negative effects associated with disaster management technology have been identified: primarily the potential of information overload and the dissemination of incorrect and outdated information [8, 18].

2.1.1 Social Media and Disasters

The history of online communities is firmly linked to disasters. Internet Relay Chat (IRC) was one of the first truly global online communication systems; its adoption among internet connected citizens was 'prompted by the First Gulf War' [19]. Although radio and television broadcasts were halted by the Iraqi army shortly after the invasion, IRC communication continued for days afterward. IRC allowed users to communicate about conditions on the ground, including the gulf war oil spill that grew to be the largest oil spill in history [20].

The history of social media and the hashtag is invariably linked to disaster communication. It was during the San Diego bush fires of 2007 that the hashtag was first widely used on twitter [19].

Quarantelli emphasized that ‘management of hazards is fundamentally social in nature and not something that can be achieved strictly through technological upgrading’ [10] yet social media brings human behavior into a machine readable format that can be used to provide further information during disasters.

Much work has been done in passively listening to social media streams in order to better understand how disasters unfold and how humans use social media as a communication tool during disaster events. Many of these studies use hand labeled tweets in order to classify what kind of information people talk about [21].

Further work has evolved to using artificial intelligence methods to automatically label new tweets using supervised learning. For example, Patrick Meier’s Haiti Crisis Map initially used volunteers to classify large number of tweets, but his more recent projects focus on the use of AI for tackling big data problems [5].

2.1.2 Crowdsourcing vs. Passive Listening

As Patrick Meier points out in *Digital Humanitarians*, ‘since humanitarian organizations don’t ask eyewitnesses on social media to report information’, they must passively wait and ‘rely on witnesses sharing relevant information by chance’ [5]. Listening to twitter data streams and hoping that someone posts relevant disaster information is not always a winning strategy. One solution to this problem is to have paid workers that collect information and enter it into disaster information systems as in [9], which details how paid workers were used to input data from citizens during the Mozambique floods of 2007; however, this method is expensive and does not scale well. The same report states that ‘data processing and consolidation [were] difficult’ and that ‘the few data entry clerks struggled to keep up’ [9].

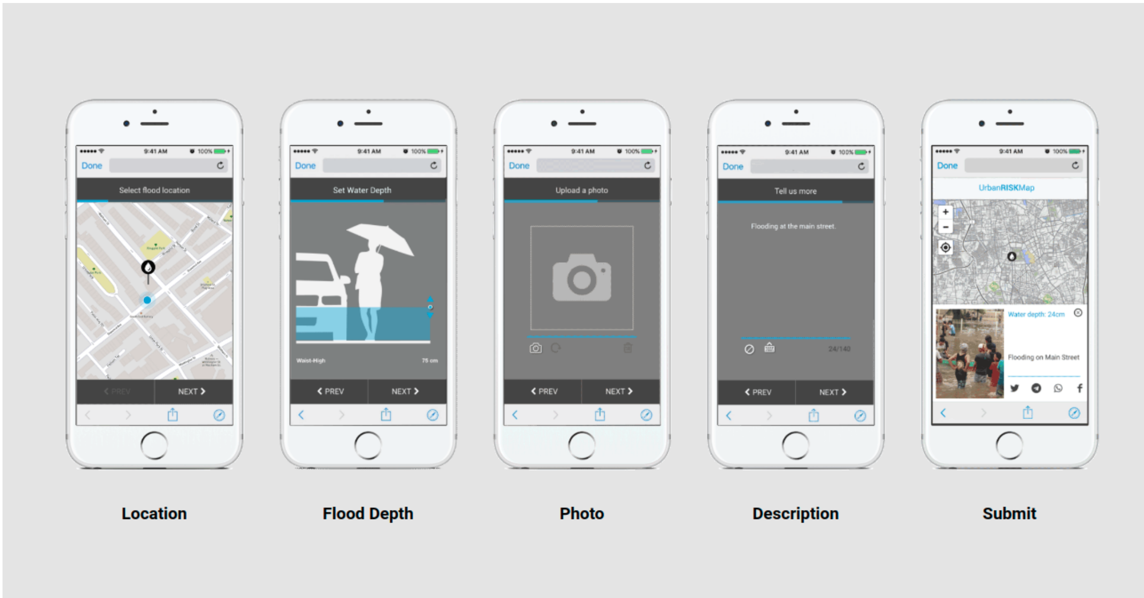

Figure 2-1: Submitting a flood report card

2.2 The Riskmap System

The Riskmap system alleviates the load on emergency managers by centralizing reports from many social media sources. It also makes it easy not only for reports to come into the response center, but also for emergency managers to indicate which areas of a city are most affected at any one time. The data gathered during an event is persistent and available under the Creative Commons license, which allows researchers to track the flood over time and pinpoint areas that are particularly vulnerable to flooding, thus fulfilling the need for open data [22, 23].

The system has been in place in Jakarta and Chennai since 2016, and has seen hundreds of thousands of views during flood events [24, 25].

2.2.1 Social Media Outreach

Riskmap consists of many different social media bots that are actively filtering social media streams and looking for citizens that might be reporting flooding events, it then reaches out to those users and asks them to submit a flood report that consists of a GPS location, the estimated flood height at that location, a picture, and a textual description. The user interface for submitting these reports is shown in 2-1. These reports are then displayed on a public map for other citizens to inform themselves. Furthermore, EOC personnel are able to access the Risk Evaluation Matrix (REM), a special dashboard that allows them to give even more information to citizens.

2.2.2 Need for open data

Creating bespoke information systems at the beginning of disasters has been the norm [9]; however this means that disaster response organizations must become acclimated with the system at the same time that they are dealing with disaster situations. Researchers have shown the need to create open sourced crowdsourced emergency systems that provide open data [26]. The Riskmap System was created to fill that need.

2.3 Conquering Information Overload

When researchers have tried using social media to track real-time disasters, they often suffer from information overload. For example, Meier states that the Haiti Crisis map was 'constantly overwhelmed with the vast amount of information that needed to be monitored and processed' and that the team never 'managed to catch up' with the backlog of social media activity [5].

It is not enough to create an advanced system for consuming citizen reports, it is also necessary to ensure that this system does not consume resources that are already scarce during a disaster event, for example the time of emergency workers [9]. Furthermore, it is also important to reduce the resources needed to create insights because if analyzing data is too difficult, then decision makers will make decisions without having fully analyzed the data [3].

Using computers to automatically make sense of disaster data has long been a goal in disaster informatics, but only recently have machine learning techniques become advanced enough to be implemented in production emergency systems [5]. Image recognition algorithms can provide summaries of objects and scenes found in user submitted photos [27, 28]. Natural language processing can estimate the probability that a textual document is overall negative or positive and thereby give EOCs a shorthand way to summarize thousands of reports in short amounts of time [27, 29]. Finally, ensemble learning methods can learn relationships between disparate datasets and synthesize a single result [30].

In this work we will experiment with different machine learning techniques for image recognition, finally showing that transfer learning at the output layer can turn off the shelf multi—label classification algorithms into classifiers for flood image classification. For textual analysis, we will show the performance of bag of words, bigrams, and a combination of both techniques to classify report texts into heavy flooding/ no heavy flooding classes. Flood height will first be assessed as a raw numerical feature but will then be joined with nearby reports through a one dimensional convolutional filter in order to draw out temporal patterns. Finally, the output of these disparate techniques will be combined by using a small deep neural network to classify a report into one of two classes: 'heavy flooding' or 'no heavy flooding'

Finally, the output of these disparate techniques will be combined by using a small deep neural network. In order to allow better interpretability, the most important labels from feature extraction machine learning algorithms are presented to the user so that they can understand what drove the machine's choice.

Chapter 3

Previous Work for Machine Learning in Crisis Informatics

As discussed in Section 2.1.1, researchers have enviously eyed the panacea of information present in social media streams since the inception of the medium. Social media datasets are often very large, often hundreds of thousands or millions of data points can be collected during a single event. For example more than 1.5 million disaster related tweets were created during the 2011 Tohoku earthquake [31] and over 20 million during hurricane Sandy [5]. While all of these tweets concern the natural disaster and citizen's reaction to the event, only a few have actionable intelligence that can help Emergency Operations Systems to better respond to an event.

3.1 Passive Collection after Event

Because of the large number of data points and because of the difficulty of using humans to label all of the data set, researchers have turned to keyword searches to whittle down the volume of data [31].

Either hand label small set or use keywords to aggregate data points and examine statistics on those aggregates.

3.1.1 labeling by hand

Many studies of social media disaster data focused around post-event analysis using manual labeling. In [32] Starbird and Palen explore the uptake of the Tweek the Tweet (TtT) microsyntax, where citizens are encouraged to use a specific syntax in order to request or offer help during a crisis event. The adoption of the syntax by citizens on the ground was very low. Only 39 tweets in the TtT dataset originated within the affected areas; however, the authors saw many more tweets that were translated into the TtT syntax by other users.

Some was looking for clues after disasters: 'To make samples manageable, we reduced the data sets to those user streams that included more than three tweets containing the search terms.' [7] problem: don't have real time results

3.1.2 Machine Labeled

[33]

Problems with that approach:

It is very difficult to filter out which social media images are related to the disaster and which are not.

3.2 On Image Data

Online learning using traditional transfer learning [28] but online (so they get people to label images as a disaster happens?) plus train with generic disaster images in order to solve cold start problem at the beginning of an event. Classify social media images into 3 classes: (severe, mild, little) damage. [34]

3.3 On Text Data

Crowd sentiment detection during disasters using twitter and the 2010 San Bruno CA fires n=3698 [29]

Feature engineering on twitter messages to classify into pre-incident, during incident and post-incident [35]

Classifying tweets as informative/ not informative using CNNs vs SVMs (CNN wins) [36]

CrisisNLP from the Qatar Computing Research Institute has a huge datasets [27]

3.4 Ensemble Learning Models

Boosting of Tree-Based Classifiers for Predictive Risk Modeling in GIS [37]

This paper [30] uses deep learning to identify damage related info

Low level visual features (extract color, shape texture) + then Use bag of words on the text. Make a [38]

Hierarchical Mixtures of experts using the EM algorithm [39]

There have been some notable projects that attempt to provide complete systems that can be used for different disasters. Most notably are the Sahana and the AIDR projects.

Sahana has suspended its disaster response project that helped to mobilize volunteers to respond to disasters. // not focusing enough on the HCI and hidden wiring?

3.5 Challenges

3.5.1 Task Subjectivity

Task subjectivity is an incredibly common issue [34, 3]. While most humans can agree on whether an object is or is not an apple, this task does not translate to defining if a picture indicates a severe event or a minor one.

In other words, people's perception of risk varies widely from region to region and from citizen to citizen [3].

3.5.2 Small Datasets

Although a limited number of larger datasets have recently become available, there has historically been a scarcity of training and validation data available for Deep learning models that are trained on small datasets tend to overfit on the training data and do not generalize well to the validation dataset [40, 27].

In many early studies only hundreds of data points were considered— combined with the small size of those data points (for example, twitter microblogs of 140 or 280 characters) and effectively using deep learning becomes very difficult. For example [29] only uses 3,698 tweets in order to train

Connects citizens to EOC

As discussed in **??**, the Riskmap system helps to connect citizens to Emergency Operations Centers

Focus on technology rather than whole system design

A series of UN case studies on six disaster information systems found that while engineering and system design were essential, it was the hidden wiring of support networks that allows for technology to succeed.

> An important message emerges from the case studies: an effective disaster information management system requires a good technological platform, but also much more. Software programs for storing, sharing, and manipulating data for disasters are being developed or patched together at a steady pace, often in the aftermath of disasters. The real difficulty lies in anchoring these technological approaches in an appropriate institutional context where they are supported by relevant and effective operating procedures, agreed terminology and data labeling, and a shared awareness of

the benefits of proper handling of disaster information. Clearly, a disaster information management system must be supported by accepted rules, procedures, and relationships that encourage, facilitate, and guide the production, sharing, and analysis and use of data in response to disaster. In these case studies, the institutional dimension—the hidden wiring—determined the effectiveness of the systems. [9]

Chapter 4

Methodology and Results

The Riskmap system allows citizens to easily submit disaster reports as such it has allowed the Urban Risk Lab at MIT to gather thousands of reports of real flooding in Indonesia and India. These data points include requests for help, traffic reports, indications that an area is safe, and advice for other citizens in the area. Images attached to reports include a wide variety of scenes, from daylight highways with cars and motorcycles to night time deserted alleys. Additionally, citizens were asked to provide an estimated flood height using a slider.

4.1 Text

As shown in Section 2.2, the Riskmap system allows citizens to provide a textual description to emergency managers. In Indonesia, most of the reports are provided in Bahasa, the local language; however, in Chennai all reports were submitted in English even though the system also supports Tamil. In both Chennai and Jakarta these reports are quite brief, with the longest reports having 140 characters. In this manner, they are quite similar to tweets which were initially 140 characters but this limit was doubled in 2017. Helpfully, this means that much of the work described in 3.3 applies to the Riskmap text corpus.

Table 4.1 contains a sample of ten reports that are indicative of those found in the Riskmap textual descriptions.

pkey	text
169	Waterlogging near cathedral road flyover
171	1st street Engineers avenue
173	Not that much water safe only
174	50cm water stagnant on the road
176	Water level rising slowly
177	Water logging
178	Model school road is completely flooded, with water almost knee deep
179	Heavy rain in West mambalam flood
180	Water on roads. Stay safe
182	4cm rainfall.. still continuing.. hope for safe .. dont come outside in night time
181	Luz signal flooded knee deep water

4.1.1 Preprocessing

We first remove test reports, which are reports submitted in order to ensure that the system is working. The following POSTGRESQL query was executed to remove reports that were only used to test the system:

```
SELECT   pkey,
         text
FROM     riskmap.all_reports
WHERE    text IS NOT NULL
AND      Length (text) > 0
AND      text NOT similar TO '%%(T|t)(E|e)(S|s)(T|t)%%'
ORDER BY created_at;
```

We then use python to remove punctuation and then split along whitespace, thus splitting the source text into individual words without any spaces.

```
def prepare_text(report_text):
    '''
    returns a list of strings where each string is a different word
    '''
    import string
    exclude = set(string.punctuation)
```

```
s = "".join(ch for ch in inp if ch not in exclude )
return s.lower().split()
```

4.1.2 Sentiment analysis

Since each report in the Chennai dataset includes a textual description in English, we could use off the shelf sentiment analysis to gauge how negatively citizens are feeling. It might be the case that a highly negative sentiment corresponds to heavy flooding and that a positive sentiment corresponds to lighter or no flooding. We can investigate the relation between a negative sentiment and heavy flooding by using conditional probability. We set the threshhold for negative sentiment at .5 and then use the AWS Rekognition API in order to classify texts into heavy flooding when negative sentiment is greater than .5 and into light or no flooding otherwise.

We use bayes' rule in order to analyze the true positive rate— the probability that a report represents heavy flooding given a negative sentiment:

$$P(HeavyFlooding|negative) = \frac{P(heavyFlooding|negative)}{P(negative)} = .65$$

The false positive rate, which is the probability that there is no heavy flooding given a negative sentiment is given by:

$$P(NoFlooding|negative) = \frac{P(NoFlooding|negative)}{P(negative)} = .34$$

These probabilities show that while there is some relation between a negative sentiment and flooding, it is not a very strong signal. Furthermore, there are no off the shelf sentiment analysis tools for the Indonesian language, so a model based on AWS Rekogniton or Google Cloud Natural Language API would not translate to the

Jakarta dataset.

4.1.3 Bag Of Words

While sentiment analysis might not be a strong enough signal of heavy flooding/ no heavy flooding, our experiment shows that the textual data contains important information. In order to train a machine learning algorithm on textual data one must first create an embedding that maps natural language into feature vectors. There are many ways of creating embeddings as discussed in Section 3.3, but many of them require large datasets or do not support Indonesian. For example, word2vec is a popular embedding model that produces floating point vectors and has achieved remarkable performance; however, the size of its training vocabulary is 962,000 unique words [41]. It is possible to download a pre-trained word2vec model and use it to encode new texts, but such a pre-trained model doesn't exist for Indonesian. We could train it using a different dataset of Indonesian texts, but there is no guarantee that our domain specific words would have a good embedding after having trained with a different corpus.

The bag of words encoding is particularly attractive to the Riskmap dataset because it language agnostic and can therefore work on both the Chennai and Jakarta datasets. The bag of words approach to classifying texts consists of first creating a vocabulary that maps from a token t to a unique index i. Each report text is then encoded into a feature vector by setting the ith element to 1 if the token t exists in the report text [42].

The bag of words model correctly classifies 67 percent of reports in the Chennai corpus under 5 fold cross validation. Examining the data, we see that there are many instances of reports such as 'no flooding here' which are being misclassified because the embedding is not able to understand relationships between adjacent words.

4.1.4 Bigrams

Bigrams are an embedding that allows the separator to learn relationships between adjacent words. The vocabulary is created by using pairs of adjacent words, such that 'no flooding here' would turn into 2 tokens: 'no flooding' and 'flooding here'.

4.1.5 Both

4.2 Images

4.2.1 Visual Bag of Words

[43]

4.3 Flood Height

4.3.1 Raw

4.3.2 Normalized

4.4 Ensemble with Neural Net

In [39], Jordan and Jacobs showed that nueral networks can be effectively used to vote between different classifiers that are effictive only in their specific domain of the space. They present a case for using the Estimation Maximization (EM) algorithm for optimizing the weights of the neural network. Hierarchical mixtures of experts and the EM algorithm [39] + bishop p. 673 [44]

Chapter 5

Future Work

5.1 Individual

5.1.1 Image Data

Using transfer learning

As the time goes on and the Riskmap System registers more flood events, more data will be collected. One possible method that is not explored in this work is the use of transfer learning inside of an image classifier neural network as in [28].

5.1.2 Text Data

word2vec

As outlined previously, we did not experiment with word2vec embeddings because of the difficulty of handling multi language datasets; however, it would be possible to create a word2vec embedder for Indonesian by using publicly available texts such as Wikipedia.

5.1.3 Flood Height

5.1.4 Location Information

5.2 Ensemble Methods

5.2.1 Bigger network

Our current bagging network is very small so as to reduce over fitting on the small datasets we currently have. As the Riskmap System collects more data, it is likely that we can use a larger network with a decreased risk of over fitting.

Appendix A

Tables

Table A.1: Armadillos

Armadillos	are
our	friends

Appendix B

Figures

Figure B-1: Armadillo slaying lawyer.

Figure B-2: Armadillo eradicating national debt.

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